Market-State Dependent Momentum Strategies: An Empirical Examination of Anomalies in Asset Pricing

Arnau Rodon Comas*
Universitat Pompeu Fabra, Barcelona, Spain
University of Essex, Colchester, United Kingdom

This study examines the profitability of a market-state dependent momentum-reversal strategy and its implications for asset pricing anomalies. Utilizing a dataset spanning 1940 to 2023 from the Center for Research in Security Prices (CRSP), we construct a dynamic trading strategy that switches between momentum and reversal regimes based on market conditions. The empirical results demonstrate that the strategy consistently generates significant abnormal returns, challenging the weak-form Efficient Market Hypothesis (EMH). Factor model regressions against the Fama-French five-factor model, along with additional momentum and long-term reversal factors, confirm that the strategy captures return patterns unexplained by conventional risk-based models. The findings align with behavioral finance theories, suggesting that investor biases and structural market constraints contribute to sustained price trends and reversals. While the study highlights the robustness of a conditional momentum strategy, limitations such as transaction costs and market frictions require further exploration. These results contribute to the broader discussion on market efficiency and the dynamic nature of asset pricing anomalies, offering practical insights for quantitative investors and portfolio managers.

*Undergraduate Student, Universitat Pompeu Fabra, Exchange Student at University of Essex. Email: rodonarnau@gmail.com

I. Introduction

The Efficient Market Hypothesis (EMH), first formalized by Fama [1], posits that asset prices fully reflect all available information, rendering systematic excess returns unattainable without assuming additional risk. Despite the theoretical elegance of this framework, empirical studies have repeatedly identified anomalies that contradict its predictions. Among the most well-documented are momentum—the tendency of past winners to continue outperforming—and reversals, where long-term losers tend to generate excess returns compared to long-term winners over future periods.

Jegadeesh and Titman (1993) [2] first documented momentum strategies in the U.S. stock market, demonstrating that stocks with high past returns continue to outperform those with low past returns over intermediate horizons. Subsequent research has extended this finding across different markets and asset classes (Griffin, Ji, & Martin (2003) [3]; Moskowitz, Ooi, & Pedersen (2012) [4]. Conversely, De Bondt and Thaler (1985)[5] identified the reversal effect, showing that assets with extreme past underperformance tend to revert to their mean over multi-year periods. These anomalies challenge the weak-form EMH by suggesting that past prices contain predictive information about future returns.

A growing body of research suggests that the profitability of momentum and reversal strategies is conditional on broader market dynamics. Cooper, Gutierrez, and Hameed (2004) [6] found that momentum strategies are significantly more profitable following periods of strong market performance but weaken in bear markets. Hwang and Rubesam (2007) [7] further demonstrated that momentum profitability varies over time, influenced by economic and liquidity conditions. These findings imply that the effectiveness of trading strategies depends on the prevailing market state, introducing the possibility of dynamically adapting between momentum and reversal approaches.

This study contributes to the existing literature by empirically testing a market-state dependent momentum-reversal strategy. Using historical return data, we classify market states based on past cumulative performance and implement a regime-switching approach. During positive market states, the strategy follows a traditional momentum framework (long winners, short losers), while in negative market states, it switches to a contrarian reversal approach (long losers, short winners). This approach seeks to optimize returns by exploiting the conditional profitability of these anomalies.

To evaluate the robustness of the strategy, we conduct factor model regressions using the Fama-French five-factor model, alongside momentum and long-term reversal factors. The key objectives of this study are:

1) To examine whether a market-state dependent strategy generates superior risk-adjusted returns compared to a static momentum approach.
2) To determine if the returns are explained by conventional risk factors or represent an independent pricing anomaly.
3) To assess the implications of market-state dependency for asset pricing and investment strategies.

Our results indicate that the proposed strategy significantly outperforms traditional momentum approaches, with an economically and statistically significant alpha. These findings highlight persistent inefficiencies in financial markets, supporting behavioral explanations for momentum and reversal anomalies. Additionally, they offer practical applications for portfolio managers and algorithmic traders seeking to enhance risk-adjusted returns.

The remainder of this paper is structured as follows: Section 2 reviews the existing literature on momentum, reversals, and market efficiency. Section 3 details the data and methodology used in constructing the strategy. Section 4 presents the empirical results, including portfolio performance and factor model analysis. Section 5 discusses the broader implications of the findings, while Section 6 concludes with potential directions for future research.

II. Literature Review

The study of momentum anomalies and their relationship with market efficiency has been a key topic in financial research for decades. The Efficient Market Hypothesis (EMH), as formalized by Fama (1970) [1], asserts that asset prices fully reflect all available information, making it impossible to consistently achieve excess returns without assuming additional risk. Despite this theoretical foundation, empirical evidence suggests the presence of persistent return anomalies, with momentum and reversal effects among the most widely documented.

A. Momentum Anomalies

One of the earliest and most influential studies on momentum strategies was conducted by Jegadeesh and Titman (1993) [2], who demonstrated that stocks with high past returns (winners) tend to outperform those with low past returns (losers) over intermediate horizons of three to twelve months. Their analysis, based on the NYSE and AMEX data from 1965 to 1989, showed that a zero-cost portfolio—long in winners and short in losers—consistently generated statistically significant abnormal returns. This evidence directly challenges the weak-form EMH, which asserts that past prices should not predict future returns. Subsequent research has confirmed the robustness of momentum anomalies across various asset classes and market environments. Griffin, Ji, and Martin (2003) extended the momentum framework to international equity markets, demonstrating its persistence across both developed and emerging economies. Meanwhile, Moskowitz, Ooi, and Pedersen (2012) introduced the concept of time-series momentum, showing that assets with positive past returns continue to exhibit strong performance over time in equities, commodities, and bonds. These findings suggest that momentum is not merely a statistical irregularity but a pervasive phenomenon in financial markets.

B. Reversal Anomalies

In contrast to momentum, long-term reversals suggest that assets experiencing extended periods of underperformance tend to outperform in subsequent periods. De Bondt and Thaler (1985) provided one of the first empirical demonstrations of this effect, showing that past losers (over a three-year horizon) significantly outperformed past winners over subsequent periods of similar length. They attributed this pattern to behavioral biases, particularly investor overreaction, where extreme negative price movements lead to excessive pessimism, causing subsequent corrections.

Further research has reinforced the existence of short-term (1-month) and long-term (3 to 5 years) reversals. Jegadeesh (1990) [8] and Chopra, Lakonishok, and Ritter (1992) [9] documented that these reversals are particularly strong among stocks that experienced extreme prior underperformance, suggesting that mean reversion in stock prices plays a crucial role. More recently, Asness, Moskowitz, and Pedersen (2013) [10] integrated momentum and reversal effects into a broader framework, arguing that both anomalies can be understood from a combination of risk-based and behavioral perspectives.

C. Market-State Dependency in Momentum and Reversal Strategies

Momentum profitability has been found to be contingent on market conditions, implying that the effectiveness of momentum strategies is not uniform across different market regimes. Cooper, Gutierrez, and Hameed (2004) [6] introduced the concept of market-state dependent momentum, demonstrating that momentum effects are significantly stronger following positive market returns but weaken or even reverse after negative market conditions. Their findings suggest that the performance of momentum strategies is influenced by broader economic cycles and investor sentiment.

Building on this idea, Hwang and Rubesam (2007) [7] extended the analysis, showing that momentum anomalies fluctuate across different market regimes, reinforcing the notion that momentum strategies are conditional on liquidity constraints and economic cycles. These results are consistent with Daniel, Hirshleifer, and Subrahmanyam (1998) [11], who proposed that investor overconfidence and biased self-attribution contribute to momentum profitability during bull markets but diminish during bearish conditions. Such insights highlight the dynamic nature of price trends and suggest that market efficiency is not absolute but conditional on prevailing market conditions.

D. Factor Models and the Integration of Momentum and Reversal

In response to the observed anomalies, asset pricing models have evolved to include additional factors beyond market risk. The seminal work of Fama and French (1993) [12] introduced the three-factor model, incorporating size (SMB) and value (HML) factors alongside the traditional market risk factor (MKT) from the Capital Asset Pricing Model (CAPM). This model significantly improved explanatory power in explaining cross-sectional returns. Further refinements led to the Fama-French five-factor model (2015) [13], which introduced profitability (RMW) and investment (CMA) factors to capture additional dimensions of asset pricing.

However, despite these advancements, momentum remains largely unexplained within standard factor models. Carhart (1997) [14] extended the Fama-French framework by introducing a four-factor model, which includes a momentum factor (MOM) that captures returns from a zero-cost winners-minus-losers portfolio. While this model improves explanatory power, it still does not fully explain the persistence and variation of momentum profits across different market states.

Similarly, long-term reversals have been analyzed within factor models by constructing long-short portfolios based on multi-year return horizons (De Bondt & Thaler (1985) [5]). The inclusion of a reversal factor alongside momentum has provided a more comprehensive framework for understanding return anomalies, though challenges remain in fully integrating these effects into traditional risk-based models.

E. Conclusion

The existing literature highlights the persistence of momentum and reversal anomalies despite advancements in asset pricing models. The conditional nature of momentum strategies, particularly their dependency on market states, suggests a more nuanced understanding of market efficiency. This study contributes to the ongoing discourse by testing a dynamic momentum-reversal strategy that adapts to prevailing market conditions, examining its profitability relative to established factor models and behavioral explanations.

III. Data & Methodology

A. Data Source

This study employs an extensive dataset obtained from the Center for Research in Security Prices (CRSP), covering the period from January 1940 to December 2023. The dataset includes all common stocks (share codes 10 and 11) listed on the NYSE, AMEX, and NASDAQ, ensuring broad market coverage. To mitigate potential survivorship bias, the dataset retains securities that have been delisted or temporarily suspended, allowing for a more representative analysis of market dynamics over time.

B. Strategy Construction

Following the methodology of Jegadeesh and Titman (1993) [2], stocks are ranked into deciles based on their prior J-month returns. A zero-cost momentum strategy is constructed by taking long positions in the top decile (winners) and short positions in the bottom decile (losers). The strategy is rebalanced monthly, with positions liquidated after K months to establish an overlapping portfolio framework. This study primarily examines a 12-month formation and 3-month holding period, though alternative formation-holding period configurations are also tested as robustness checks to assess the strategy's sensitivity to parameter selection.

To introduce market-state dependency, the market condition is defined using the sign of the past 24-month cumulative return of the CRSP value-weighted index. Under this approach, a positive cumulative return indicates a positive market state that triggers the traditional momentum strategy (long winners, short losers), whereas a negative cumulative return signals a negative market state, prompting a reversal approach (long losers, short winners). This dynamic allocation allows the strategy to capitalize on momentum effects during strong markets while exploiting reversal tendencies in downturns, enhancing adaptability to changing market conditions.

The choice of a 24-month lookback period is grounded in both theoretical and empirical considerations. Previous work by Cooper, Gutierrez, and Hameed (2004) demonstrated that momentum profitability is highly sensitive to the lookback period used for market-state classification—with shorter horizons reflecting more transient trends and longer horizons capturing deeper structural cycles. Their framework evaluated market conditions using 12-, 24-, and 36-month lookback periods. Our analysis over the sample period (1940–2023) reveals that a 12-month lookback results in 77 market state changes, suggesting that it may be overly responsive to short-term noise. In contrast, a 36-month lookback produces only 18 state changes, indicating that it is too sluggish to capture timely shifts in market conditions. The 24-month lookback, which yields 47 state changes, strikes a balance by smoothing out high-frequency fluctuations inherent in the 12-month measure while remaining responsive enough to detect intermediate-term shifts that a 36-month measure might overlook. This balanced approach ensures that both temporary market fluctuations and broader economic cycles are effectively captured, enhancing the dynamic switching mechanism of the strategy. Furthermore, robustness tests employing alternative lookback periods (12- and 36-months) are conducted to verify the stability and sensitivity of this classification.

C. Rolling 30-Year Window Computation for Performance Metrics

To evaluate the long-term performance and stability of the strategy—and to mitigate the effects of short-term volatility—we compute key performance metrics (average monthly excess return or monthly alpha value, and t-statistics) using a rolling 30-year window approach. In this framework, each computed metric is based on a continuous 30-year period. For example, the metric reported for January 1940 is calculated as the average monthly excess return or monthly alpha value (and its corresponding t-statistic) over the period from January 1940 to December 1969. The window then shifts forward by one month so that the value for February 1940 reflects the period from February 1940 to January 1970. This monthly rolling procedure continues until we reach the final window, which ends 30 years before the most recent available month (i.e., 30 years before December 2023).

This method provides two primary benefits. First, by averaging performance over a long period, we reduce the influence of short-term market noise and transient events. Second, it offers a continuous, evolving perspective on the strategy's performance, capturing the persistent effects of market conditions and structural changes over time. This 30-year rolling window is applied both in our replication studies and when assessing portfolio performance, ensuring that every reported average metric and t-statistic reflects a comprehensive long-run view.

D. Factor Model Analysis

To evaluate the performance and risk exposure of the market-state dependent strategy, multifactor regression analysis is conducted using the Fama-French five-factor model (Fama & French (2015) [13]) with additional momentum and long-term reversal factors. The dependent variable in the regression model is the excess return of the market-state dependent strategy, while the independent variables include:

- Market risk premium (MKT-RF): Captures overall market exposure.
- Size (SMB): Accounts for the size effect (small vs. large stocks).

- Value (HML): Reflects the value premium (value vs. growth stocks).
- Profitability (RMW): Measures the impact of firm profitability.
- Investment (CMA): Controls for differences in corporate investment policies.
- Momentum (MOM): Captures return persistence of past winners vs. losers.
- Long-term reversal (LT-R): Accounts for multi-year mean-reversion effects.

Statistical significance is assessed through t-statistics, and rolling window regressions are performed to examine time-varying dynamics. Robustness checks include alternative market-state definitions (12- and 36-month lookbacks) and variations in formation/holding periods. This methodological framework ensures that the market-state dependent momentum-reversal strategy is rigorously tested against established asset pricing models. By incorporating dynamic adjustments based on market conditions, this approach provides valuable insights into the conditional nature of momentum and reversal effects and their implications for market efficiency and portfolio management.

IV. Empirical Results

This section evaluates the performance of the market-state dependent momentum-reversal strategy, replicates previous findings, and compares the results to traditional momentum strategies. We assess the profitability, risk-adjusted returns, and relationship with established asset pricing models. Key findings are presented through portfolio performance metrics, factor model regressions, and robustness tests.

A. Studies Replication

To validate the original findings of Jegadeesh and Titman (1993) [2], we replicate their traditional momentum strategy over the same sample period (1965–1989). Figure 1 reports the cumulative logarithmic excess returns, confirming that the strategy was indeed profitable during this period.

However, when we extend the analysis to a broader timeframe (1940–2023), as depicted in Figure 2, the profitability of the traditional momentum strategy declines significantly post-2000, which motivates our conditional strategy approach. This observation not only aligns with the findings of Hwang and Rubesam (2007) [7], who documented a similar deterioration in momentum profits in more recent decades, but also underscores an important market evolution: momentum effects that were once robust seem to have weakened or even dissipated in more recent decades.

To further analyze this decline, Figures 3 and 4 report the average monthly excess return using 30-year rolling windows, and the t-statistic confirming whether returns are statistically different from zero. Consistent with Figure 2, these long-term metrics reveal a pronounced decrease in momentum profitability after 2000, with the statistical significance of excess returns progressively diminishing over time. This observed erosion in the performance of the traditional momentum strategy provides a compelling rationale for developing a conditional approach—one that dynamically adjusts between momentum and reversal regimes based on prevailing market states—to better capture persistent return anomalies in evolving market environments.

B. Portfolio Performance and Statistical Significance

Figure 5 presents the cumulative logarithmic excess returns of the market-state dependent momentum-reversal strategy in the timeframe 1940-2023. Unlike the traditional momentum approach, this adaptive strategy does not exhibit a significant decline in profitability over time.

The key performance metrics indicate that the market-state dependent approach generates an average monthly excess return of 1.03% with a t-statistic of 4.82, confirming statistical significance at the 1% level. Figures 6 and 7 report the average monthly excess returns and their associated t-statistics, computed using our 30-year rolling window method. These results show that the market-state dependent strategy consistently achieves positive excess returns, with an average monthly excess return exceeding 0.6% (7.4% annualized) across all subperiods. Furthermore, the t-statistic remains above 1.96 for nearly the entire sample, reinforcing the robustness of the strategy's profitability over time.

C. Factor Model Regression Analysis

To assess whether the observed excess returns are explained by known risk factors, we regress the strategy's returns on the Fama-French five-factor model and an extended seven-factor model that includes momentum (MOM) and long-term reversal (LT-R) factors. Using 30-year rolling windows, Figures 8 and 9 present the estimated alpha from the five-factor regression, showing monthly alpha ranging from 0.3% to 1.3%. The alpha exceeds the 1% monthly average over the last 15 years, confirming persistent profitability. The corresponding t-statistics range between 0.7 and 2.9, with values above 2.2 over the last 18 years, indicating strong statistical significance in the last 2 decades. These results suggest that the strategy generates excess returns that cannot be fully explained by traditional risk factors, particularly in recent periods. If we regress the returns of the strategy with a 7 factor model, based on the original Fama-French five-factor model, but including the Fama-French momentum and long-term reversals factor, the results are similar. Figures 10 and 11 report the estimated alpha. Monthly alpha ranges from -0.5% to 1.2%, with values exceeding 0.75% over the last 15 years, confirming continued profitability. The t-statistic ranges from -1.8 to 2.7, but remains above 2.0 for most of the last 15 years, demonstrating statistical significance. Table 1 presents factor loadings for the seven-factor regression over the full sample period (1940–2023). The results indicate a positive and significant loading on MOM (0.43, t = 6.41), confirming a strong relationship with momentum effects, and significant exposure to market risk (MKT-RF, 0.22, t = 3.35). The negative coefficient on LT-R (-0.33, t = -2.33) suggests a negative relationship with long-term reversals. The significant alpha of 0.006 (t = 2.43) support our claim that the market-state dependent strategy captures return patterns not fully explained by conventional risk factors. However, we recognize that the use of overlapping portfolios can induce autocorrelation in the residuals of our regression models.

D. Robustness Tests

To ensure robustness, we conduct additional tests using alternative market-state definitions (12- and 36-month cumulative returns) and varying formation/holding periods (3-,6-,9- and 12-months) over the time frame 1940-2023. Table 2 reports the average excess return and t-statistics across different specifications, confirming profitability in 37 out of 48 configurations, with t-statistics above 2.0. Notably, 8 out of the 11 cases that do not achieve statistical significance originate from a formation period of 3 months, which aligns with the expectation that shorter formation periods may not fully capture the mid-term nature of the momentum effect (typically observed in the 3 to 12-month range). Table 3 analyzes the estimated alpha and statistical significance across different specifications with the 7 factor model. 10 out of 48 cases yield a t-statistic above 1.96, confirming statistical significance at the 5% level for its positive alpha value. An additional 13 cases exhibit t-statistics between 1.6 and 1.96, indicating near-significance, which may still be relevant in practical investment applications.

The empirical results demonstrate that a market-state dependent momentum-reversal strategy outperforms traditional momentum strategies, particularly in volatile market conditions. The strategy remains statistically and economically significant despite the decline in traditional momentum profitability and captures unique market inefficiencies not fully explained by conventional asset pricing models. Robustness tests confirm that the strategy maintains profitability across various market-state definitions and parameter configurations, reinforcing its validity as an adaptive investment strategy. These findings highlight the importance of dynamic market conditions in shaping momentum and reversal profitability, offering both theoretical insights for financial economics and practical applications for quantitative investors.

V. Conclusion

A. Discussion

The empirical findings suggest that market-state dependent momentum strategies generate significant abnormal returns beyond those explained by traditional factor models. The ability of the strategy to adapt between momentum and reversal regimes provides a more dynamic approach to capturing asset mispricing. A key implication of these results is that market efficiency is not uniform across time but rather conditional on prevailing economic conditions. The strong alpha observed, even after controlling for the Fama-French five-factor model and additional momentum and reversal factors, suggests the existence of persistent inefficiencies that traditional risk-based explanations fail to capture. This aligns with behavioral finance theories, which argue that investors' cognitive biases and market constraints contribute to prolonged price trends and reversals.

The strategy's performance underscores the importance of flexibility in investment approaches. Traditional momentum strategies, while historically profitable, tend to underperform in bearish markets. By dynamically adjusting exposure based on market state, investors can mitigate drawdowns associated with momentum crashes while capitalizing on opportunities presented by reversals. Despite these promising findings, certain limitations must be acknowledged. The effectiveness of the strategy depends on the accuracy of market state definitions, and different lookback periods may yield varying results. Additionally, transaction costs and market frictions were not explicitly accounted for in the analysis, which could impact real-world implementation.

Future research could explore alternative definitions of market states beyond cumulative returns, such as volatility regimes or macroeconomic indicators. Furthermore, integrating machine learning techniques to optimize switching criteria between momentum and reversal could enhance the robustness of the strategy. Overall, the results contribute to the ongoing debate on market efficiency and asset pricing, offering evidence that conditional strategies can generate superior risk-adjusted returns by systematically adapting to evolving market conditions.

B. Conclusion

This study provides empirical evidence supporting the effectiveness of a market-state dependent momentum-reversal strategy. By dynamically adjusting between momentum and reversal approaches based on prevailing market conditions, the strategy achieves superior risk-adjusted returns compared to traditional momentum strategies. The results challenge the weak-form Efficient Market Hypothesis under certain market conditions, highlighting persistent inefficiencies in asset pricing.Nevertheless, it is important to temper this conclusion by considering alternative explanations for the observed results. Regression analysis against the Fama-French five-factor model and additional momentum and reversal factors confirms that the strategy's alpha remains statistically significant, suggesting that it captures return patterns unexplained by conventional risk-based models. The findings align with behavioral finance theories, which propose that investor biases and structural market constraints contribute to sustained price trends and reversals.

While the study presents strong empirical evidence, limitations remain. The robustness of market-state classification methods requires further testing, and real-world implementation challenges, such as transaction costs and liquidity constraints, should be addressed. Future research could explore machine learning approaches for optimizing regime-switching criteria or investigate the strategy's performance in alternative asset classes and global markets. This research contributes to the ongoing discussion on market efficiency and asset pricing anomalies, demonstrating that conditional strategies can enhance portfolio performance by systematically adjusting to evolving market conditions.

References

[1] Fama, E. F., "Efficient capital markets," *Journal of finance*, Vol. 25, No. 2, 1970, pp. 383–417.

[2] Jegadeesh, N., and Titman, S., "Returns to buying winners and selling losers: Implications for stock market efficiency," *The Journal of finance*, Vol. 48, No. 1, 1993, pp. 65–91.

[3] Griffin, J. M., Ji, X., and Martin, S. J., "Momentum Investing and Business Cycle Risk: Evidence from Pole to Pole," *Journal of Finance*, Vol. 58, No. 6, 2003, pp. 2515–2547.

[4] Moskowitz, T. J., Ooi, Y. H., and Pedersen, L. H., "Time series momentum," *Journal of financial economics*, Vol. 104, No. 2, 2012, pp. 228–250.

[5] De Bondt, W. F., and Thaler, R., "Does the stock market overreact?" *The Journal of finance*, Vol. 40, No. 3, 1985, pp. 793–805.

[6] Cooper, M. J., Gutierrez Jr, R. C., and Hameed, A., "Market states and momentum," *The journal of Finance*, Vol. 59, No. 3, 2004, pp. 1345–1365.

[7] Hwang, S., and Rubesam, A., "Market-State Dependent Momentum," 2007.

[8] Jegadeesh, N., "Evidence of predictable behavior of security returns," *The Journal of finance*, Vol. 45, No. 3, 1990, pp. 881–898.

[9] Chopra, N., Lakonishok, J., and Ritter, J. R., "Measuring abnormal performance: do stocks overreact?" *Journal of financial Economics*, Vol. 31, No. 2, 1992, pp. 235–268.

[10] Asness, C. S., Moskowitz, T. J., and Pedersen, L. H., "Value and momentum everywhere," *The journal of finance*, Vol. 68, No. 3, 2013, pp. 929–985.

[11] Daniel, K., Hirshleifer, D., and Subrahmanyam, A., "Investor psychology and security market under-and overreactions," *the Journal of Finance*, Vol. 53, No. 6, 1998, pp. 1839–1885.

[12] Fama, E. F., and French, K. R., "Common risk factors in the returns on stocks and bonds," *Journal of financial economics*, Vol. 33, No. 1, 1993, pp. 3–56.

[13] Fama, E. F., and French, K. R., "A five-factor asset pricing model," *Journal of financial economics*, Vol. 116, No. 1, 2015, pp. 1–22.

[14] Carhart, M. M., "On persistence in mutual fund performance," *The Journal of finance*, Vol. 52, No. 1, 1997, pp. 57–82.

Table 1 Factor loadings for the seven-factor regression over the full sample period (1940-2023). The results indicate a positive and significant loading on MOM (0.43, t = 6.41), confirming a strong relationship with momentum effects, and significant exposure to market risk (MKT-RF, 0.22, t = 3.35). The negative coefficient on LT-R (-0.33, t = -2.33) suggests a negative relationship with long-term reversals. The significant alpha of 0.006 (t = 2.43) demonstrates that the strategy captures return components not fully explained by traditional risk factors.

Coefficient	Value	t-Statistic	p-Value
const	0.006863	2.429563	1.536125e-02
Mom	0.429257	6.413644	2.576370e-10
Rev	-0.325202	-2.331485	2.000361e-02
Mkt-RF	0.227624	3.350366	8.492583e-04
SMB	-0.060287	-0.585072	5.586834e-01
HML	0.240648	1.787227	7.432252e-02
RMW	-0.023219	-0.171678	8.637391e-01
CMA	0.064499	0.321003	7.483018e-01

Table 2 Average excess returns and t-statistics across different specifications for three market-state lags (Lag: 12, 24, 36). For each formation and holding period combination, the first row reports the mean return and the second row reports the corresponding t-statistic.

Formation Period	Holding Period	Statistic	Lag 12	Lag 24	Lag 36
3	3	Mean Return	0.002008	0.002943	0.002486
		t-stat	1.176868	1.730046	1.459782
3	6	Mean Return	0.002804	0.004393	0.004105
		t-stat	1.903773	3.002589	2.801624
3	9	Mean Return	0.002516	0.004263	0.004064
		t-stat	1.858595	3.178206	3.024782
3	12	Mean Return	0.001930	0.004162	0.003683
		t-stat	1.658033	3.625206	3.197301

Continued on next page

Table 2 Continued

Formation Period	Holding Period	Statistic	Lag 12	Lag 24	Lag 36
6	3	Mean Return	0.005675	0.007615	0.007023
		t-stat	2.793203	3.771114	3.471808
6	6	Mean Return	0.005565	0.007891	0.007423
		t-stat	2.967926	4.244226	3.985965
6	9	Mean Return	0.004586	0.007361	0.006785
		t-stat	2.776480	4.509648	4.146654
6	12	Mean Return	0.002707	0.005659	0.005068
		t-stat	1.782058	3.770364	3.367671
9	3	Mean Return	0.007068	0.009772	0.009082
		t-stat	3.212735	4.478958	4.154690
9	6	Mean Return	0.006294	0.009526	0.008710
		t-stat	3.206727	4.910113	4.477029
9	9	Mean Return	0.004221	0.007581	0.006892
		t-stat	2.314071	4.204528	3.812957
9	12	Mean Return	0.002382	0.005392	0.004641
		t-stat	1.394569	3.187079	2.736480
12	3	Mean Return	0.006886	0.010289	0.009038
		t-stat	3.189603	4.815665	4.215718
12	6	Mean Return	0.004949	0.008561	0.007758
		t-stat	2.431415	4.250724	3.842567
12	9	Mean Return	0.003005	0.006369	0.005550
		t-stat	1.559472	3.336219	2.900695

Continued on next page

Table 2 Continued

Formation Period	Holding Period	Statistic	Lag 12	Lag 24	Lag 36
12	12	Mean Return	0.001501	0.004349	0.003538
		t-stat	0.821134	2.396105	1.944983

Table 3 Estimated alpha (Const) and t-statistics using the 7-factor model for three market-state lags (Lag: 12, 24, 36). For each formation and holding period combination, the first row reports the estimated alpha and the second row reports the corresponding t-statistic.

Formation Period	Holding Period	Statistic	Lag 12	Lag 24	Lag 36
3	3	Const	0.001202	-0.000749	-0.001503
		t-stat	0.538283	-0.338038	-0.692283
3	6	Const	0.001950	0.001378	0.000714
		t-stat	0.984551	0.705508	0.372065
3	9	Const	0.001963	0.001968	0.001279
		t-stat	1.076579	1.104148	0.732323
3	12	Const	0.001092	0.002023	0.001304
		t-stat	0.698436	1.331086	0.875946
6	3	Const	0.004847	0.003843	0.002859
		t-stat	1.790130	1.427062	1.078666
6	6	Const	0.004823	0.004913	0.003988
		t-stat	1.913516	1.976760	1.632191
6	9	Const	0.003649	0.004873	0.004011
		t-stat	1.642699	2.243825	1.880333
6	12	Const	0.001864	0.003592	0.002655
		t-stat	0.914035	1.800502	1.353935
9	3	Const	0.006764	0.006933	0.005678
		t-stat	2.306097	2.392679	1.993381
9	6	Const	0.005355	0.006894	0.005789
		t-stat	2.034892	2.674382	2.282953

Continued on next page

Table 3 Continued

Formation Period	Holding Period	Statistic	Lag 12	Lag 24	Lag 36
9	9	Const	0.003452	0.005580	0.004459
		t-stat	1.408845	2.332066	1.895344
9	12	Const	0.001901	0.003682	0.002492
		t-stat	0.828905	1.643199	1.130058
12	3	Const	0.005248	0.006863	0.005573
		t-stat	1.830006	2.429563	2.003960
12	6	Const	0.003760	0.006056	0.004790
		t-stat	1.381890	2.268261	1.822654
12	9	Const	0.002393	0.004530	0.003183
		t-stat	0.926240	1.792873	1.279478
12	12	Const	0.001094	0.002606	0.001251
		t-stat	0.447524	1.089687	0.530438

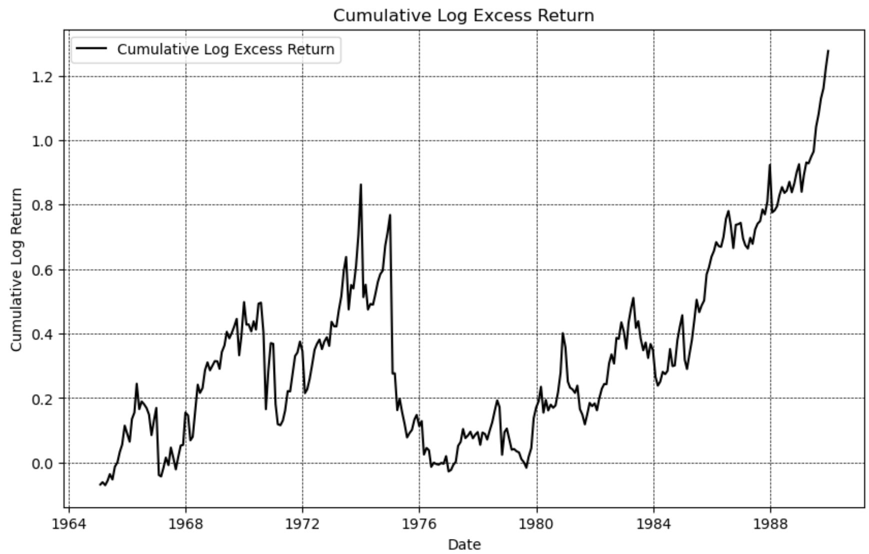

Fig. 1 Cumulative log excess return over the period 1965–1989. The plot shows the cumulative sum of monthly log excess returns, indicating persistent trends in return patterns. The strong upward trend from 1982 onward highlights a period of sustained positive excess returns.

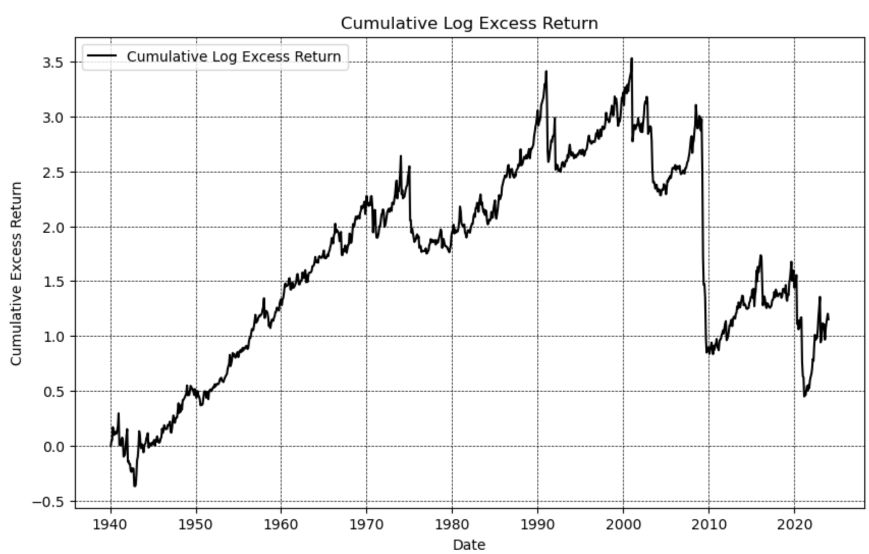

Fig. 2 Cumulative log excess return from 1940 to 2023, showing strong persistence until the early 2000s, followed by a sharp decline, particularly during the 2008 financial crisis.

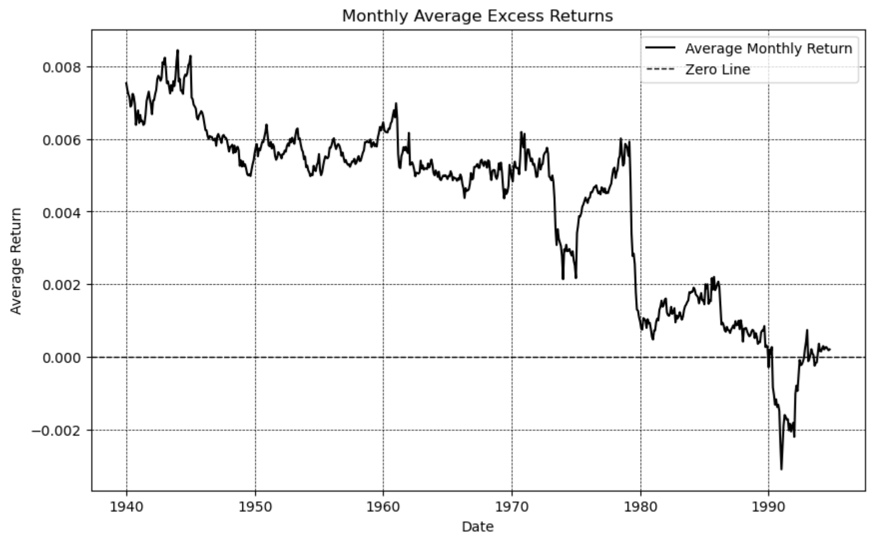

Fig. 3 Monthly average excess returns computed using a 30-year rolling window over the period 1940–1994. Each data point represents the average monthly excess return calculated over a complete 30-year window (e.g., the value for January 1940 reflects performance from January 1940 to December 1969, with the window advancing monthly until the final window ending in December 1994).

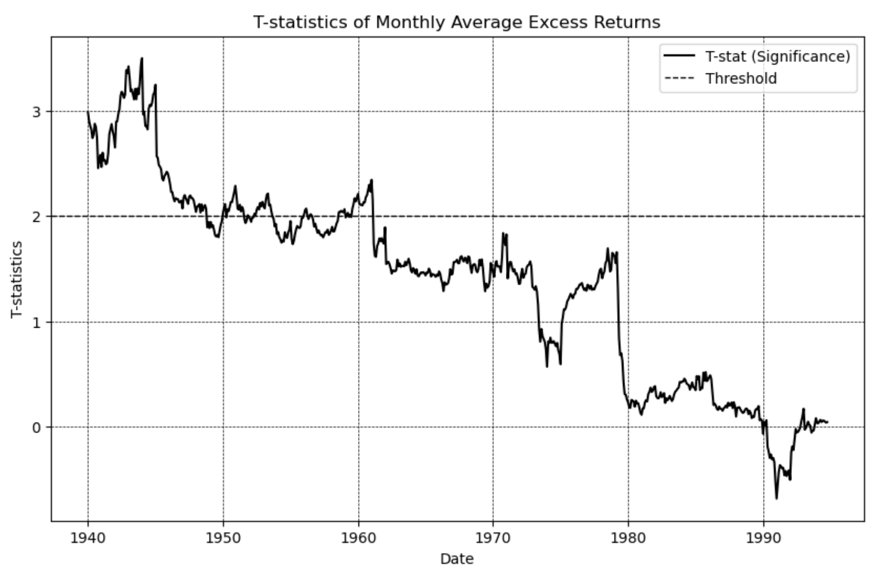

Fig. 4 T-statistics of monthly average returns computed using a 30-year rolling window over the period 1940–1994. The dashed line indicates the significance threshold of 2.0, highlighting periods with statistical momentum or risk-premium effects, such as during the 1940s.

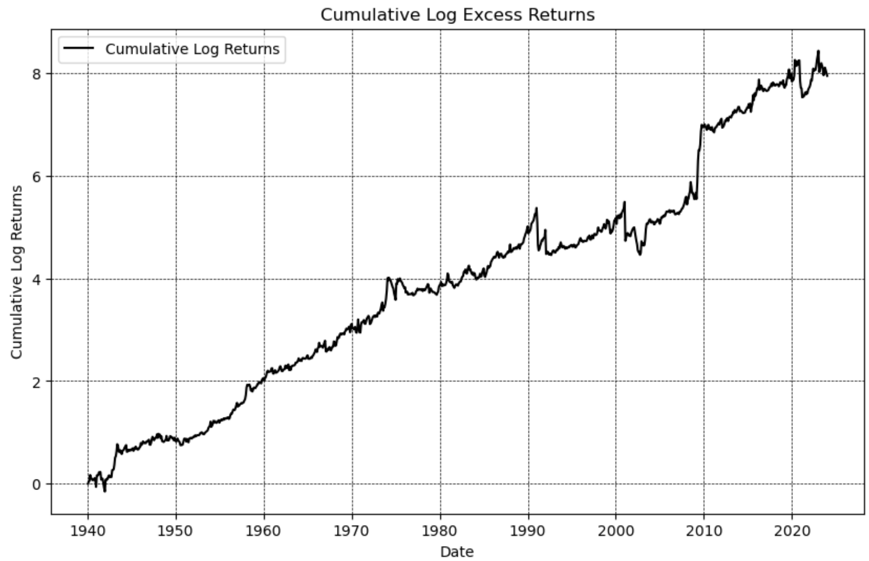

Fig. 5 Cumulative log returns from 1940 to 2023. The long-term trend in cumulative log returns suggests strong compounding effects.

Fig. 6 Monthly average excess returns computed using a 30-year rolling window over the period 1940–1994. The pattern highlights return anomalies with a persistent positive average return over the entire sample period.

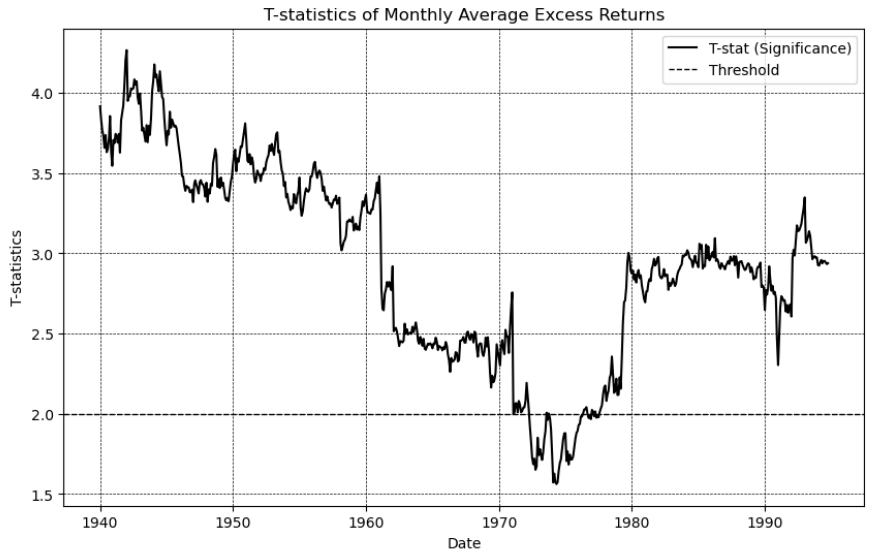

Fig. 7 T-statistics of monthly average excess returns computed using a 30-year rolling window over the period 1940–1994.

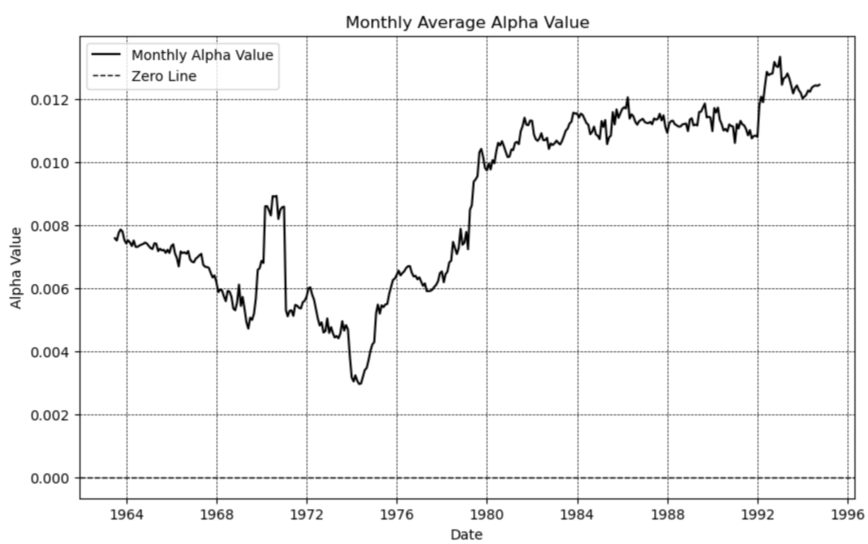

Fig. 8 Monthly average alpha values computed using a 30-year rolling window over the period 1964–1994 based on the Fama-French five-factor model. The results indicate periods of strong positive alpha, particularly after 1980, suggesting potential market inefficiencies or additional risk premiums not captured by standard asset pricing models.

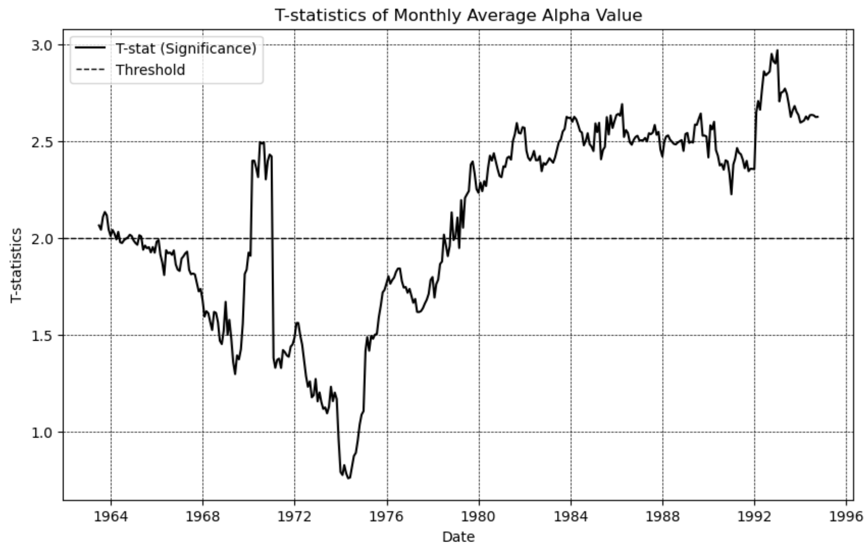

Fig. 9 T-statistics of monthly average alpha values computed using a 30-year rolling window over the period 1964–1994 based on the Fama-French five-factor model. The dashed line indicates the 2.0 significance threshold, highlighting sustained periods of statistically significant alpha that reinforce the presence of unexplained return components after 1980s.

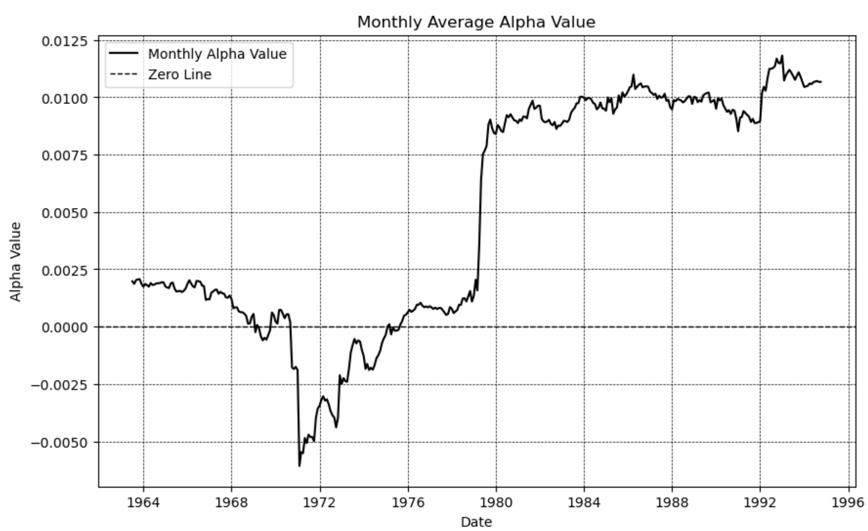

Fig. 10 Monthly average alpha values computed using a 30-year rolling window over the period 1964–1994 based on the extended seven-factor model, which incorporates momentum (MOM) and long-term reversal (LT-R) factors. Although the inclusion of additional factors slightly reduces alpha magnitudes, a positive trend is maintained post-1980, suggesting persistent return anomalies.

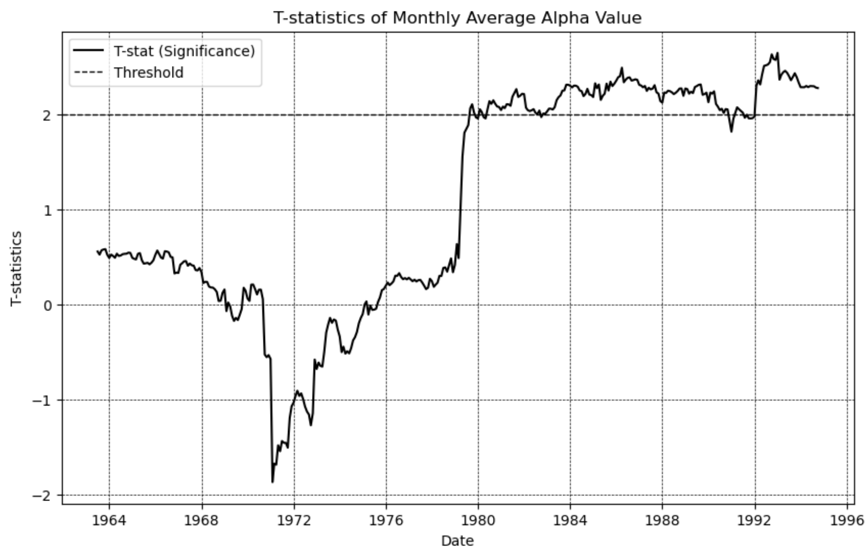

Fig. 11 T-statistics of monthly average alpha values computed using a 30-year rolling window over the period 1964–1994 based on the extended seven-factor model. The results indicate statistically significant alpha values in several periods, with the strongest effects observed after 1980, thereby supporting the robustness of the market-state dependent strategy.